Looking Beyond the Firm-specific Determinants of New Technology Diffusion: An Analysis of Advanced Manufacturing Technology Adoption in Indian Automotive Industry[1]

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1. INTRODUCTION

The dynamics of world manufacturing have changed dramatically over the recent years primarily due to the development and diffusion of new technologies[2] and the integratedness of world economies spurred by globalization. While the former has permeated vast effects on organizations (viz., changing the ways organizations function and interact with others), the latter has largely imbued the nature of industrial activities by changing the structure and geographic distribution of world industrial production. These two forces, often interactively, are affecting the manufacturing industry in more than one way. While competition has become more intense than ever before, it is waged over not only price factors but also a number of non-price attributes (like quality, speed and flexibility etc.,) and evolving customer preferences alongside. The evolving market conditions and customer requirements are acting upon the firms to prompt them to be increasingly flexible and responsive. Under these conditions, the adoption of new technologies such as advanced manufacturing techniques[3] (AMTs), due to their enormous implications on production[4], is critical to the manufacturing firms world wide, but more so for the developing country firms who are facing fierce challenges from their developed counterparts in this globalized world order. Diffusion[5] of new technologies like AMTs, though critical for the firms, is not ubiquitous in developing countries who have several odds stacked against them in the form of poor infrastructure, weak development base and other structural bottlenecks. Arguably, the characteristics of their industry structure, organisation and the health of the economy interact in a complex way in determining the firm-level adoption of new technologies.

[1] This paper is a part of my Ph.D dissertation, which aims at modelling the diffusion of AMTs in Indian Automotive Industry. An earlier version of it was published as UNU-MERIT discussion paper. I sincerely thank Bart Verspagen and Pierre Mohnen for providing several useful comments and insights during the preparation of this paper. The financial support from WOTRO (NWO), The Netherlands is gratefully acknowledged. The scientific responsibility is however assumed by the author.

[2] They refer primarily to information and communications technologies (ICT) and a host of other ICT-enabled technologies after the micro-electronics revolution in the 1970's.

[3] Advanced manufacturing techniques, also broadly called as 'flexible automation techniques', refer to all kinds of microelectronics-based technologies that enable the application of computers in production environments (e.g., NC/CNC machine tools, computer aided design/manufacturing, flexible manufacturing systems etc. AMTs are regarded as the technologies of highest economic significance in modern day manufacturing.

[4] The use of AMTs reportedly result in significant improvements in inventory levels, quality, and its cost, space requirements, lead and cycle times, scrap and yield rates, and a number of other measures (Meredith, 1987).

[5] The terms 'diffusion' and 'adoption' are used interchangeably in our text as from a micro (firm) perspective both refer to the same thing.

Taking note of these idiosyncrasies of a developing economy like India[6], in this paper we intend to investigate the adoption pattern of AMTs and the factors affecting the mechanics of their diffusion.

The process of diffusion of (new) technologies has been a widely debated area with scholars from different disciplines trying to analyse the process from their respective angles in order to map out a clear understanding of the underlying dynamism. Several theories have been put forward to interpret patterns of new technology adoption and a series of empirical studies have followed to operationalize and measure the importance as well as the direction of these theoretical strands.[7] Understandably, far from being linear and atomistic, diffusion process involves a complex core that characterises artful coordination among socio-economic agents faced with ever new challenges in evolving market set-up. This recognition, originating mainly from the systemic perspective of innovation, puts interaction among firms and their specificities concerning the patterns of interaction in the system as the core of innovation. From a microcosmic perspective, diffusion is nothing but an innovation process as it involves a complex combination of innovation and adaptation. Taking this broader perspective of diffusion, the aim of the paper is to understand and explain the causations underlying the process of diffusion. The specific aim of this paper is to address the possible set of factors determining adoption of new technologies such as Advanced Manufacturing Techniques (AMTs) in the Indian automotive industry (more specifically, the component segment). Building on both the early 'epidemic' and the later 'equilibrium' theories of adoption, our analysis is purported to provide an empirical exploration of determinants of adoption that takes into account the influence of structural, (i.e., firm-specific), and socio-economic factors on the process of adoption and to examine the effects of the various explanatory variables on adoption pattern.

The empirical analysis is based on firm-level data on the Indian auto component industry obtained from both primary and secondary sources. In congruence with the recent studies of technology adoption in the literature (e.g., Karshenas and Stoneman, 1995; Arvanitis and Hollenstein, 2001, etc.,), the general framework of our analysis is specified where we distinguish a series of explanatory variables. The paper is set up as follows. Section 2 provides a brief background of the Indian automotive industry describing its development and current scenario. The next section (Section 3) traces the theoretical roots of the diffusion literature followed by a discussion of the determinants of adoption in section 3. Section 4 outlines the empirical framework of our analysis, where we introduce the empirical model and the variables and describe the nature and sources of data. Following this, Section 5 presents and discusses the empirical results. Section 6 summarises the overall findings.

[6] The manufacturing firms in developing countries like India are trapped in the snare of 'demand for faster development, competitiveness and facing both technically-sophisticated and not-so-advanced domestic/foreign customers'.

[7] Since the seminal contributions of Griliches (1957) and Mansfield (1961), the study of the causes, and consequences of new technology adoption has drawn enormous interests from economists. See Stoneman (1983); Metcalfe (1988); Rogers (1995) for surveys of literature on diffusion.

2. A SNAPSHOT OF INDIAN AUTOMOTIVE INDUSTRY

The automotive industry plays a pivotal role in India's economy, both by directly contributing a major share to the GDP, and indirectly but noticeably, by stimulating growth in other core sectors of the economy.[8] India has also an extensive and rapidly expanding automotive components industry[9], which is widely perceived to be the next industry, after software to becoming globally competitive. The availability of highly skilled and educated workforce (primarily English-speaking managers), low-cost manufacturing base and the partnering linkages with global supply chain are some of the advantages that lend the Indian component industry an edge over many other developing countries.

The industry, which had started production in a small way in as early as 1940s was not in harmony with the global industry due to low volumes and high protective policies of the government till very recent period. The industry has crossed many milestones since. But the biggest, rather paradigmatic change in the structure came about with the establishment of Maruti Udyog Limited (MUL), a joint venture between Government of India and Suzuki Motors Corporation of Japan in the early 1980s. The economic reforms that followed in the eighties and nineties paved the way for greater heights of success for the industry. The industry has thus been exposed to the Japanese technology and product standards since the advent of MUL and later in time, to the advanced technologies of many of the international automotive firms such as – Ford, Hyundai, Daewoo, General Motors, Peugeot, and Toyota etc. At present, the auto component industry manufactures the entire range of parts required by the domestic automobile industry. Most components required by the Indian automobile industry are manufactured locally. Import dependence is very low and is restricted to items requiring special steels and materials or precision engineering.

Within the last decades the industry metamorphosed into a relatively high-growth and dynamic one following the buoyant rise of the automotive industry.[10] The strong growth in volumes of vehicles produced and the entry of global auto manufacturers and in some case, their parts suppliers into India impinged on the dynamics of the components industry in various ways. Several trends are notable.

First, there has been a rapid spurt of production, investment and exports (see Figure 1). Between 1996-97 and 2004-2005 auto-component production rose annually by about 18 percent while investment increased at an annual rate of 15 percent. During the span of nine-years, exports in the auto-components sector also grew sharply, at an average annual rate of 42 percent in the mid-to late 1990s, rising about 5 times from a modest value of US$ 291 millions in 1996-97 to about US$ 1400 million in 2004-5. Going by the current trend, the

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8 This industry contributes about four percent to the Indian GDP (Source: www.ibef.org).

9 The industry structure is primarily composed of an organized sector (which contributes about 80 percent of the total industry output) and a vast unorganized sector comprising of more than 5000 firms. The organized sector which has about 425 firms serving more than 20 big vehicle manufacturers is highly consolidated at the top with nearly 50 leading companies accounting for a major share of output.

10 The output (in the passenger car segment of the industry) tripled in the past decade, rising by more than 200% in nine years from a total production of 202,000 cars in 1993-94 to 606,088 cars sold in 2002-03. The industry is currently producing about 8.4 million vehicles out of which, the passenger car segment now constitutes about 15% of the total production (behind two-wheelers which have a massive 77% of the market share (" Indian Automotive Industry: Current Status", 2005-2006 at http://acmainfo.com).

auto component industry is observed to export more than 15 percent of its output every year (ACMA, 2005).

Second, the direction of exports from India shows a remarkable change after the liberalization (see Figure 2). For instance, while before 1993, bulk of auto component exports were targeted to the non-OECD countries, since 1994 OECD countries account for the largest share of India's components exports.[11] This clearly hints at the improving competitiveness of the component suppliers.

Third, the endowment of potential low-cost manufacturing along with high engineering skills workforce has attracted a large inflow of foreign direct investment into the automotive and components sector. This was primarily due to the 'follow sourcing' strategies of the global manufacturers present in India who encouraged their group companies or suppliers to create manufacturing base in India, often in the form of joint ventures with Indian suppliers.[12] The entry of global OEMs and demand for high quality/technology components encouraged Indian auto component companies to enter into several foreign collaborations. At present, there are over 450 collaborations with foreign partners from around the world out of which 60 percent are technical collaborations (ACMA, 2003). With the growing pace of economic reforms, collaborations are on the rise, which promises a better prospect as more foreign firms are showing exceeding interest in the investment in Indian automotive sector.[13]

Fourth, linked to the previous, the improved quality of the component suppliers is reflected in increasing number of quality certifications obtained by component manufacturers. Most impressively, 81% of the small and medium firm dominated membership of the Automotive Component Manufacturers Association has the ISO 9000 certification, nearly half have the QS 9000 certification and a growing number (10%) have the ISO 14000 certification (Tewari, 2003).

Fifth, a gradual tieraisation of the industry following the global trend is marked. This has given rise to assemblers consolidating their suppliers in order to make their production process leaner. By the end of the decade of liberalization, the two major auto assemblers in India (MUL and TELCO[14]) had streamlined most of their first-tier suppliers.[15] Moreover,

[11] Currently, of the total auto component exports, developed markets such as the US and Europe together account for about 56 percent, Asia accounts for 27 percent and Africa accounts for 11 percent of the export earnings (ACMA, 2004).

[12] However, this particular trend has also raised concern as many studies have documented how such FDI can progressively undermine and marginalize the ability of domestic suppliers to penetrate increasingly closed and tight global supply networks of the multinationals that are locating in their regions (Barnes and Kaplinsky, 2000; Humphrey, 2000).

[13] The attractiveness of Indian industry has seen some major foreign investments in the industry recently. Toyota has set up a gear box plant near Bangalore which will supply manual transmission gear-boxes to its world-wide markets having annual production capacity of 160,000 units. Hyundai has built its plant with a total investment of $1bn in Chennai. The Hyundai plant has a capacity to make 250,000 cars and 350,000 engine transmission units per annum from where it has been exporting engines and transmissions to its operations in Korea and Turkey. Fiat's India operation is working towards becoming a global sourcing hub for components with already exporting components to its operations in South Africa (Source: www.ibef.org)

[14] Tata Engineering and Locomotive Company (TELCO) is the largest indigenous conglomerate in the Indian automotive industry. Known widely as Tata Motors, the company produces a wide range of Commercial Vehicles, Passenger Cars and Multi-Utility Vehicles.

the increasing trend of sourcing many integrated assemblies rather than components which put the large and competent component suppliers next to the assemblers while the technologically weaker firms were relegated to lower rungs of the value chain.

Thus a clear hierarchical structure started emerging in the industry with more pressure on the lower-tier firms to climb up the value chain through technological upgrading. The expansion of car manufacturing in turn encouraged the development of the automobile component firms and emphasized localization of components and other input materials, through collaborative efforts with vendors for the development of automobile components. In a nutshell, progress of Indian automotive and auto component industry provides a positive example of globalization. However, the industry's growth and dynamism critically rests on auto component suppliers being able to produce customized components for the 'increasingly FDI-dominated' (except TELCO) auto assemblers or adapting those produced by global suppliers. And raising the quality standards, improved process capabilities, and operational excellence remain the key to this. The rising exports while has given Indian companies increasing stakes in the global sourcing, at the same time they became aware of their technological capabilities in the "global industry" (Okada, 2004). The stiff competition thus forced the firms to upgrade their quality in order to sustain competition and improve their standing in the international and domestic market. Therefore technological upgradation in terms of adoption of new technologies like AMTs needs to complement the process so as to put the industry at par with the world leaders.

3. THEORETICAL BACKGROUND

3.1 Revisiting Diffusion Literature

The diffusion of a new technology is known to be a gradual, dynamic process. In fact, new technologies are not adopted *en masse*. Rather, adoption usually begins with a few early adopters, followed by a more rapid period of adoption, with the rate of adoption saturating once most potential users have adopted the technology. The resulting path of diffusion is therefore characterized by an S-shaped curve. The earliest theory of diffusion is traced to the 'epidemic' model professed in the seminal work of Griliches (1957) and Mansfield (1968, 1989). Generally called as the 'disequilibrium' approach, the idea underlying this theory is that adoption of a new technology critically depends on the information asymmetries[16]. In the initial phases the adoption rate is slow due to the lack of information. As information spreads, the rate of adoption speeds up over time leading eventually to a phase where all the potential users adopt the technology. Evidently, incomplete information gives rise to the delay in adoption. Using the analogy of a contagious disease to describe the process of adoption – the more people "infected" by the technology, the more likely

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[15] For instance, studies note that MUL consolidated its supplier base from 404 to about 300 first-tier suppliers in a period of just two years in late nineties while TELCO followed the suit by reducing the number of suppliers from 1200 to about 500 in 1997 (Okada, 2004).

[16] This approach is called as the disequilibrium approach as in this line of argument diffusion is understood to be a self-propagating adjustment process to a fixed end point; the process of adjustment being driven by uncertainty reduction due to information spreading as a result of usage.

that others will also be "infected", economists often describe the process of diffusion as an epidemic.

The recent theoretical fervour (as in Stoneman, 1986; Karshenas and Stoneman, 1993; Sarkar, 1998), widely known as the 'equilibrium' model of adoption[17] establishes that the diffusion path is generated in which, the timing of adoption is entirely explained by objective changes in the profitability of using a new technology. Dearth of information does not constrain diffusion, and contagion effects are ruled out a priori as sources of information and influence upon adopter perceptions. Thus, in contrast to the epidemic models where information drives the process of diffusion, the equilibrium models are based on the assumption that there is no information asymmetry and potential adopters behave optimally in the sense that at any point in time those who find the adoption profitable to them acquire the technology. For this reason these models are also called decision-theoretic models.[18]

The equilibrium models have been classified as rank, stock and order effects models (Karshenas and Stoneman, 1993)[19]. The *rank* effect derives from probit models (Davies, 1979; Ireland and Stoneman, 1985) – potential adopters are ranked by their gross benefits, and those with the greatest benefits go first. In these models potential adopters of a technology have different inherent characteristics and consequently obtain different gross returns from its use. These different characteristics generate differences in adoption among firms. *Stock* and *order* effects relate to the cumulative number of adopters. Both deal with strategic interactions – those who adopt faster face less competition and receive first mover advantages. As a result, early adopters gain greater net benefits than later adopters. The essence of stock effects models (Reinganum, 1981a,b, 1989; Quirmback, 1986) is that benefits to the marginal adopter from the use of new technology decreases as the number of adopters increases. Acquisition of newer technologies by firms leads to a fall in the production costs, which in turn leads to a reconfiguration of the industry output, thereby affecting the profitability of further adoption. As Karshenas and Stoneman (1993) and Kerr and Newell (2003) show that the percentage of firms already adopting the technology negatively affects the probability of adoption, which they attribute to these first-mover advantages. In the order effects models (Ireland and Stoneman, 1985; Fudenberg and Tirole, 1985), the return to a firm that adopts a new technology depends upon its position in the order of adoption implying that higher order adopting firms receive a greater return than lower order adopters.

In a way the three different variants of the equilibrium approach are similar to each other. For instance, the stock model is essentially the same as the rank models as the 'threshold'

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[17] The underlying ground of these models is that at any point in time the adoption extends only to the point where it is profitable (or most profitable) to adopt the technology, thereby ensuring equilibrium at each point on the diffusion path.

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[19] As illustrated by Karshenas and Stonemen (1993, 1995), and Baptista (2000) it is possible to subsume alternative theories of diffusion into one encompassing model. The specification of an encompassing model then enables one to test empirically which (if any) of the epidemic, rank, stock, and order effects play significant role in the diffusion process.

in the latter becomes endogenous in case of the former (being dependent on the number of adopters itself). Again the order effects models are somewhat similar to the rank models of adoption as in both sets of models the gross returns to a firm adopting new technologies depends on the position of the firm. However, studies (e.g., Baptista 2000) notes that the results of stock and order effects will be opposite on the probability of adoption. The stock effect focuses on the equilibrium number of adopters and the subsequent lower profitability of adoption, whilst order effects stress on the anticipation of future adoptions. Hence, the stock effect has a negative impact on the probability of adoption, and the order effect has a positive impact.

The existing empirical literature on technology diffusion closely follows the theoretical developments in the field. Thus while the earlier works relied mostly on the epidemic learning models (e.g., Mansfield, 1963, 1968 etc), the later works were more in the line of equilibrium models (Davies, 1979). Stoneman (1981) constructed a more explicit decision-theoretic model to analyse the process of diffusion. The more recent studies are based on advances in the theoretical modeling that takes into account the rank, stock and order effects in addition to the epidemic learning framework (e.g., Karshenas and Stoneman, 1995).

Taking the lead from these recent advances in inter-firm diffusion modeling, in this paper we combine the features of both types of framework in order to investigate the adoption process of advanced manufacturing techniques in the Indian auto component industry. Recent work on diffusion use duration models to combine features of both of epidemic and equilibrium frameworks (e.g. Kerr and Newell, 2003, Snyder et al., 2003). Our investigation does not refer to duration models of technology adoption, as we do not have information on the adoption dates. Instead, our model is tested on data relating to the adoption of AMTs at a given point in time[20]. Therefore, our empirical model explains the probability of adoption of AMTs as a function of variables, which reflect firm characteristics and information effects brought out by epidemic and other effects. Due to the cross sectional nature of our data and the absence of a time domain, we cannot use the number of adopters at any time and its variation over time to proxy for the stock and order effects. However, it may be pointed out that stock and order effects can be understood in the rank effects tradition as an endogenous phenomenon (dependent on the number of adopters) and hence we could also reflect on these from our model's primary emphasis on rank effects.

3.2 Principal Determinants of Adoption

As discussed above, diffusion is driven mainly by the changes in the gross (or net profitability). Much of the intuition on technology adoption logically extends to the AMTs. A firm which plans to adopt a certain AMT first evaluates the relative benefits and costs of adoption and accordingly makes the decision to either adopt or not. Several factors influence the firms' evaluation of the returns from the technology. The characteristics of the firm, its internal resources to effectively implement the technology, its position in the market and so on are the crucial factors which go into the firms' evaluation of the returns

[20] The data for the present analysis pertains to the year 2002-2003.

from the use of the technology. Similarly, a firm's links with external information sources greatly enhances its knowledge pool as well as its ability to evaluate the technology by learning from others' experience. These varied factors can be grouped into several homogeneous categories. For the sake of convenience we group the potential factors which influence (positively or negatively) a firm's decision to adopt AMTs under the following headings:

(i) Internal resources and absorptive capability of the firm

Economics of innovation emphasises differences in firms technological and organisational resources and competencies as the crux of difference in innovation abilities of the firms (e.g., Freeman, 1988). In the literature, firm size has been traditionally regarded as a crude measure for the extent to which a firm may be said to be resource-rich. The importance of firm size upon the innovation effort and its success for a firm has a long history and classical flavour to it (Schumpeter, 1942). It is argued that large firms have multiple production sites and a larger base of experience with various technologies that can help the adoption of new process technologies. Moreover, established large firms have an advantage in the capital markets and therefore can marshal greater resources quickly than smaller firms in adopting and implementing a new technology. Therefore, firm size can act as a major determinant of adoption. In most of the studies on adoption behaviour firm size often stands for many firm-specific effects (financial resources, range of activities, etc.) and /or functions as a proxy for other variables on the model when it is strongly correlated with them (size-dependent models).

Another related variable, firm age has also been posited to be an important factor determining the decision to adopt new technologies. However, like other earlier studies have mentioned, the impact of firm age on adoption is difficult to predict a-priori because of the presence of two opposing effects (e.g., positive impact reflecting specific experience of old firms vs. a negative effect due to lower adjustment costs in relatively new firms with a more modern capital stock besides the more openness of managers of newer firms towards new technologies).

The firm's ability to absorb knowledge from external sources and use it in its innovative activities have been long associated with firm's innovativeness in general and technology adoption in particular (see Cohen and Levinthal, 1989; Baldwin and Rafiquzzaman, 1998). A skilled and educated work force enhances the absorptive capability of a firm (Cohen and Levinthal, 1989). This is because the endowment of human and knowledge capital within a firm determines the firm's overall ability to assess technological opportunities in (or around) its fields of activity. The endowment of human capital can be proxied by the percentage of technical and managerial staff among the employees. The higher the proportion of trained technical/ managerial employees, the greater is their ability to absorb the knowledge around them within and outside the firm. Therefore this variable is expected to be positively related to adoption. Another crucial dimension of absorptive capacity is R&D. Investment in R&D directly contributes to the absorptive capability of the firm, which increases the likelihood of adoption of advanced process technologies.

(ii) Demand and market conditions

A potential factor that can affect the innovation/ adoption behaviour of the firms is related to the (product) market conditions under which the firms are operating. The Schumpeterian tradition of innovation asserts the positive effects of market concentration on innovation of firms. In the game theoretic literature, the competitive pressure in the face of the firms has long been recognised as an important motivator of innovation. Market concentration is generally taken as a structural variable to reflect the competitive pressure prevailing in the industry. It is shown that on the one hand, competitive pressure might accelerate adoption (as marginal benefits are higher for an early adopter), while on the other, this may result in each firm capturing less of the post adoption market and so may not encourage adoption (Reinganum, 1981a,b). Another line of thought in line with Kamien and Schwartz (1970) goes argues that a greater competitive pressure might result in higher demand elasticities (due to availability of close substitutes in the market) and therefore drive firms to innovative activity or faster adoption of new technologies (see e.g., Majumdar and Venkataraman, 1993). The possibility of a nonlinear (an inverted-U shape) relationship between market structure (competition) and innovation was also hinted at by Scherer (1967), who showed a positive relationship between patenting activity and firm size in the cross section, but interestingly, a diminishing impact at larger sizes when allowing for nonlinearities.

The net effect of market concentration on adoption has thus been quite ambiguous as it is hard to resolve theoretically whether positive effects market concentration in the tradition of Schumpeter outweighs the negative effects of free competition (Reinganum, 1981a,b,c; Arvanitis and Hollenstein, 2001). Therefore we don’t predict any sign for this variable and leave this to the empirical verification.

(iii) Perceived benefits (incentives) of adoption

A third group of variables relates to a set of anticipated benefits (perceived by the firms) from adopting the AMTs. In fact, much of the economic intuition on technology adoption follows from the argument of Mansfield (1968, 1989) that firms adopt new technologies based on their expected profits from adoption[21]. The programmable automation technologies like AMTs are characteristically flexible which makes them suitable to produce at a range of output levels. Moreover, the use of AMTs may lead to increase in product quality or better conditions for product development (Arvanitis and Hollenstein 2001) in addition to increasing the flexibility of the production process. In addition, it has been argued that the use of these technologies may lead to reduction in costs. For example, the new technology may save some specific labour skills that are unavailable or are hard to acquire by the firm; it may reduce capital requirements through say, reduction of inventories, increased utilisation of the equipments etc. The advantages of using AMTs, may, thus broadly include higher flexibility, improvement in product quality, and savings of cost from input use, general cost reduction, etc.

A number of earlier researchers (Carlsson, 1989; Piore and Sabel, 1984 etc.) have patronised AMTs as being well suited to meet high technical-flexibility requirements of the firms, especially those specialising in manufacturing a diverse array of parts or products in

[21] For example, Mansfield (1989) explains the diffusion of industrial robots on the basis of differences in firms’ estimates of their own profitability of adoption.

small batches. Because AMTs can be reprogrammed for each change in product, a firm producing such products will have a greater propensity to adopt the technology as it lowers the switching costs of products. Hence firms with high flexibility requirements should have a greater likelihood of adoption. In previous research on new technologies such as programmable automation, firms have reported that reductions in direct labour costs or increased productivity are the major gains from adopting this process innovation (Kelley and Brooks, 1991).

(iv) Linkages to external sources

By external linkages we refer to the firms' link with other firms (suppliers, customers, competitors), institutions (universities, research institutes, financial institutions, government regulators etc). This can be understood in the form of co-operation of the firms. As argued in the systemic notion of innovation, the innovation process is highly interactive- and a greater cooperation among firms and among firms and other institutions generates synergies, which furthers innovation.

There are multiple external resources by which a firm can acquire knowledge, or to be more specific, information about a new technology and it's utility to the firm's operations. Written sources of communication viz., publications and other communications from machinery suppliers and their distributors constitute an important external source of learning about AMTs. Nevertheless, by itself, this kind of linkages with knowledge sources does not seem to be a sufficiently reliable means of influencing AMT adoption. Therefore we don't expect to find any substantial difference among AMT adopters and non-adopters with respect to their reliance on such written sources of communication. Knowledge exchange in the form of informal interchange of information through conversations with production managers and engineers of other firms can be an important factor. This type of knowledge exchange is recognised a s a sort of 'individualized form of learning". In line with earlier studies (Kelley and Brooks, 1991; Stoneman, 1980), we do expect to find a positive effect of this form of knowledge exchange on the likelihood of adoption of AMTs. Trade fairs and other organised activities of the firms where they are exposed to the operational details of the various technologies provide a great source of leaning for the firms. These forums provide avenue for managers and engineers from firms to interact and learn about the new technologies. We would therefore expect that firms with such linkages have a higher propensity to adopt AMTs.

In light of the various determinants listed above, the next section formalises the empirical framework of our study.

4. EMPIRICAL FRAMEWORK

4.1 Methodology

In the econometric literature, discrete choice models are frequently employed to analyse adoption behaviour. Three specific models of interest in this context have been: the linear probability model (LPM), the logistic function (logit) and the normal density function (probit) models. Linear probability models have several inherent problems, the most important being its very formulation.[22] Logit and probit models, being an improvement over the LPM are therefore appropriately used in the analysis of adoption process in the empirical analyses. There is no real reason to prefer one to the other as both logit and probit models produce identical results with small samples. The models are similar except that the logit is based on logistic distribution while for the probit, the distribution function is normal (the tails of the distribution are less fat). These models involve dichotomous dependent variable whose probabilities, conditional upon explanatory variables are modelled. When dependent variables are polychotomous and can be ordered into mutually exclusive categories, ordered logit/probit models are used.

For the empirical verification of determinants of adoption, in this paper, we have estimated both logit and ordered logit models.[23] The decision to adopt or not to adopt a new technology can be statistically modelled by logit regression, where the dependent variable is a binary choice variable (i.e., 0 and 1 accruing respectively to 'not to adopt' and 'to adopt') and explanatory variables may be continuous or binary in nature. Since there can be two choices, viz., decision to adopt or not adopt, then a simple logit model is relevant. However, in case the dependent variable is approximated by a set of choices, then an ordered logit model is useful. A brief exposition of the models is presented below[24].

(i) Binary Logit Model

Recall that a binary regression with (0,1) choice is represented as

$$y_i^* = \beta' X_i + \varepsilon_i \qquad \ldots (1)$$

where y_i^* is a latent variable and β' is the coefficient of explanatory variables X_i. The latent variable y_i^* is not directly observable, what is observable is a dummy variable y_i, i.e., whether a firm adopts (i.e., $y_i = 1$) or does not adopt (i.e., $y_i = 0$) a new technology. The probability of adoption is given by $p(y_i = 1) = G(\beta' X_i)$, where $G(\beta' X_i)$ is the logistic function, which is the cumulative distribution function (CDF) for a standard logistic random variable:

$$G(\beta' X_i) = \frac{\exp(\beta' X_i)}{1 + \exp(\beta' X_i)} \quad \text{or} \quad \frac{1}{1 + \exp(-\beta' X_i)} \qquad \ldots (2)$$

Since the probability of adoption, i.e., $p(y_i = 1) = G(\beta' X_i)$, the probability of non-adoption is given by $p(y_i = 0) = [1 - p(y_i = 1)] = 1 - G(\beta' X_i)$. The ratio of the two probabilities (of adoption and non-adoption) is called as the 'odds ratio', represented by:

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[22] See Maddala (1988; pp. 268-270) for an illustration of the problems associated with these models.

[23] We have used logit model as computational procedures are rather easier in this case. Moreover, the coefficients in the logit model have an immediate interpretation. A logit specification allows us to analyse in more detail the impact of each variable on adoption probabilities using odds-ratio estimates, compared with a standard probit specification.

[24] Detailed descriptions of the properties of these models can be found in standard econometric textbooks (e.g., Greene, 1999).

$$\frac{p}{1-p} = \frac{G(\beta' X_i)}{1-G(\beta' X_i)}$$
$$= \frac{[\exp(\beta' X_i)/(1+\exp(\beta' X_i))]}{1-[\exp(\beta' X_i)/(1+\exp(\beta' X_i))]} = \exp(\beta' X_i) \qquad \ldots (3)$$

In logarithmic terms, the odds ratio is given as

$$\ln \frac{p}{1-p} = \ln(\exp(\beta' X_i)) = \beta' X_i \qquad \ldots (4)$$

This is a standard logistic model, where binary dependent variable's behaviour is captured by the log-odds ratio.

The logit model, being non-linear in nature, is generally estimated by maximum likelihood (ML) method. The coefficients of the logit model, analogously to the ordinary regression coefficient, define the parameter estimates. These coefficients signify that a unit increase in the independent variable (X_i) produces β_i change in the log odds of the dependent variable (the natural log of the probability that $y_i = 1$ divided by the probability that $y_i = 0$). Positive sign for the coefficients indicate that the log of the odds ratio of adoption of AMTs increases as the value of the independent variable rises and vice versa. Because the logit coefficients are in 'log-odds' units, they are often difficult to interpret. Therefore they are usually converted into 'odds ratios' for a more intuitive explanation. Since $[p/(1-p)] = \exp(\beta' X_i)$, $\exp(\beta)$ is the effect of the independent variables on the 'odds ratio'.

Ordered Logit Model

In the ordered logit model, like the simple logit model, y_i^* is a latent variable and is not directly observable, while y_i, is observable and is now a categorical variable. For example, as in our case adoption of AMT can be defined as the 'intensity of adoption' which can fall into an ordinal category (i.e., different intensities of technology adoption, sequentially ordered from low to high). The expected model is built around the latent model (in Eq.1), where the latent dependent variable is y_i^* is related to the observed y_i in the following way:

$$\left.\begin{array}{ll} y_i = 0, \text{ if } & y_i^* < 0 \\ y_i = 1, \text{ if } & 0 \le y_i^* < \mu_1 \\ y_i = 2, \text{ if } & \mu_1 \le y_i^* < \mu_2 \\ . & . \\ . & . \\ . & . \\ y_i = j, \text{ if } & \mu_{j-1} < y_i^*, \end{array}\right\} \qquad \ldots (5)$$

where, j is the number of categories and $0 < \mu_1 < \mu_2 < ... < \mu_{j-1}$. Utilizing Equation (1) and the formulation in Equation (3), the above can now be re-written in terms of probability as follows.

$$\left.\begin{array}{l} p[y_i = 0] = p\left[y_i^* < 0\right] = p[\varepsilon < -\beta' X_i] = G(-\beta' X_i) \\ p[y_i \le 1] = p\left[y_i^* < \mu_1\right] = p[\varepsilon < (\mu_1 - \beta' X_i)] = G(\mu_1 - \beta' X_i) \\ . \\ . \\ . \\ p[y_i \le j] = p\left[y_i^* > \mu_{j-1}\right] = p[\varepsilon > (\mu_{j-1} - \beta' X_i)] = G(\mu_{j-1} - \beta' X_i) \end{array}\right\} \quad \ldots (6)$$

Replacing $G(\mu_{j-1} - \beta' X_i)$ as

$$G(\mu_{j-1} - \beta' X_i) = \frac{\exp(\mu_{j-1} - \beta' X_i)}{1 + \exp(\mu_{j-1} - \beta' X_i)} = \frac{1}{1 + \exp(\beta' X_i - \mu_{j-1})} \quad \ldots (7)$$

the ordered logit simultaneously estimates the parameter vectors β and μ using the log likelihood function. The estimated $\mu's$ indicate the dividing lines between $y_i = 0$ and 1, $y_i = 1$ and 2 and so on for the probability that an outcome is 1, 2, or more. Note that analogous to the simple logit model, we can also write ordered logit in terms of odds ratio. Denoting $p_1 = G(\mu_1 - \beta' X_i), p_2 = G(\mu_2 - \beta' X_i)$, and $p_{j-1} = G(\mu_{j-1} - \beta' X_i)$ in Eq. 7, the log-odds ratio for each category (i.e., from 1 to $j-1$) will be:

$$\left.\begin{array}{l} \ln \frac{p_1}{1 - p_1} = \frac{G(\mu_1 - \beta' X_i)}{1 - G(\mu_1 - \beta' X_i)} = \mu_1 + \beta' X_i \\ \ln \frac{p_1 + p_2}{1 - p_1 - p_2} = \frac{G(\mu_1 - \beta' X_i) + G(\mu_2 - \beta' X_i)}{1 - G(\mu_1 - \beta' X_i) - G(\mu_2 - \beta' X_i)} = \mu_2 + \beta' X \\ . \\ . \\ . \\ \ln \frac{p_1 + p_2 + ... + p_{j-1}}{1 - p_1 - p_2 - ... - p_{j-1}} = \frac{G(\mu_1 - \beta' X_i) + G(\mu_2 - \beta' X_i) + ... + G(\mu_{j-1} - \beta' X_i)}{1 - G(\mu_1 - \beta' X_i) - G(\mu_2 - \beta' X_i) - ... - G(\mu_{j-1} - \beta' X_i)} = \mu_{j-1} + \beta' X \end{array}\right\} \quad \ldots (7a)$$

where, $(p_1 + p_2 + ... + p_{j-1}) = 1$.

The ordered logits (also called as proportional odds) are thus cumulative logits that contrast categories above category j with category j and below. The ordered logit model fits only one coefficient for each X, but a separate intercept. The first (or last) is set as a reference category to which all the intercepts relate. The coefficients of ordered logits are interpreted as exactly the same way as for the binary logit model except the fact that rather than referring to a single baseline category, we contrast each category and those below it with all categories above it.

4.2 Data Description

The empirical analysis is based on firm-level data from both primary and secondary sources. The data was collected through a structured questionnaire survey of the auto component industry in India.[25] The available variables are to a large extent qualitative in nature keeping in view the research objectives. There were two main response categories: a nominal '*yes*' or '*no*' response and an ordinal scale. The respondents consist of the organised sector firms spread across three geographic regions of India viz., North, South and the West. The final data set contains 124 firms[26].

As the study refers to a point of time, the analysis is mainly cross-sectional in nature. Like similar other studies (e.g., Bartolini and Baussola, 2001), we describe technological adoption as a discrete choice typical of qualitative-dependent variable models. We model the probability of adoption of advanced manufacturing technologies as a function of a set of explanatory variables - i.e., the socio-economic determinants of new technology adoption. Below we discuss the dependent and independent variable(s) in seriatim.

4.3 Definition of Variables

(i) Dependent Variable: Adoption of AMTs

Adoption of a technology is generally understood as the current level of use and intensity of use of the technology. The dependent variable in our case is adoption of AMTs, which is treated as a binary choice variable that assumes a value 1, if adopted, 0, otherwise. In addition, we use an ordinal dependent variable to analyze the intensity of adoption of AMTs.

Based on the survey data we construct two main categories of adoption, which measure specific aspects of adoption (i.e., whether the firm has adopted or not, and the intensity of adoption). First we use the criterion 'adoption of at least one AMT' to show the current level of use of new technology. In our case as we have categorised the AMTs into three different technology groups viz., software, hardware and network communications, we use 'at least one from each technology group' as the criterion to separate the adopters from the non-adopters.

[25] The basis reference point for our questionnaire design was the advanced manufacturing technology surveys conducted by Statistics Canada for (www.statcan.ca/english/research/scilist.htm) and Arvanitis and Hollenstein (2001). Insights were also borrowed from the structure and content of CIS surveys conducted by individual countries following the OECD OSLO manual. The final survey was conducted between 2002-2003 covering all the organised sector firms (about 400) in three regions of India (North, West and South). Overall, the response rate was 32.04 percent.

[26] Given the fact that 32.04 percent is the percentage from the total population (i.e., all auto component firms in the industry in three major regions), the representation can be considered fairly good in this case. The representativeness of the sample has been confirmed by the conventional chi-square test.

Second, we also use the '*intensity*' of adoption of AMTs as a dependent variable in order to analyse the determining factors of adoption. We construct a four-level ordinal measure of AMT intensity (AMTINT) defined as the number of AMTs (out of the twelve AMTs) that are used by the firms (intensity level 1 in case of 0-3 AMTs, level 2 for 4-6, level 3 for 7-9, and 4 if more than 9 AMTs have been used). Table 1a provides specification of the dependent variables.

(ii) Explanatory Variables: Predictors of AMT Adoption

In line with our discussion on the determinants of adoption in section 3, the empirical specifications of the explanatory variables signifying the groups of factors are laid out. Table 1b provides a detailed exposition of the definition and nature of the explanatory variables used in the empirical illustration. The expected signs of impact of the variables are presented in Table 2.

The first set of variables is the various firm-specific factors which are likely to affect the adoption process. Firm size (FIRMSIZE), which should be positively related to the use of AMTs, is measured by a dummy variable related to two size classes viz., large[27] and small. Firms are defined as large or small based on their number of employees. Firms with less than 100 employees are considered as small firms and firms with more than 100 employees are considered to be large firms. Firm age (FIRMAGE) is measured by the number of years the firm has been in operation (from its year of establishment till the year of the survey)[28]. The effect of this is not predicted as the sign of this variable can vary due to the counter-balancing effects of 'long experience' vs. 'adjustment cost' effect.

The firm's pool of internal resources or absorptive capability, which is hypothesised to be positively correlated to the adoption and intensive use of AMTs, is measured by three variables in our case. The first variable included is the firm's own assessment of the level of technology (TECHLEVL), which is a combined index of the firm's technological level in its product design/development and process of production. We postulate that the firms who assess themselves highly on their capabilities are more likely to have adopted AMTs. The second variable in this category is the firm's own R&D activity (RND) that directly influences its absorptive capability. We have taken 'regular R&D performance' as the proxy for R&D activity, which is a binary variable in our case. The next one, QUALEMPL, is defined in our study as the percentage of skilled workers in the firm (employees who have formal technical and /or managerial training). This variable signals the stock of human capital, which measures the overall ability of the firm to assess the technological opportunities as well as the ability to a successful AMT implementation.

The variables under 'market conditions' represent the conditions of the product market that the firms face and their position in the industry. We have two variables in this category. The first one is the potential market base of the firm (MKTBASE), which refers to the broadness of the market served by the firm based on their Original Equipment

[27] The category large also includes the medium-sized firms.

[28] For some firms the first starting year of production is used due to non-availability of the year of establishment.

Manufacturer[29] (OEM) status. We posit that the auto component firms which serve to both domestic and foreign firms (within and outside India) will have a larger market base and therefore have a greater incentive/ propensity of adoption of new technology. Moreover, it has been claimed by empirical studies that foreign firms are more technology and quality conscious than the domestic firms in case of developing countries. Therefore, it is plausible to hypothesise that firms who are OEM suppliers to both domestic and foreign firms will adopt more. We proxy this factor by a dummy variable (see Table 1b for the construction of the variable). The second variable we use for the market conditions is the 'market concentration' variable that is proxied by the number of competitors present in the industry (as reported by the firm). This variable is also measured as a dummy variable to signify the effect of intensity of competition on adoption of AMTs. The exact direction of impact of this variable is ambiguous as greater competition might lead to higher adoption due to peer pressure where as the same might also dissuade the firms to go for heavy investments as in AMTs due to uncertain nature of their demands (e.g., the presence of more of similar firms might actually reduce the relative shares of each firm thus making the adoption of AMTs highly unprofitable to the firm)[30].

The set of variables denoting the incentives or profitability of AMT use, come from the objectives/ motives of adoption. The two variables listed under this group are obtained from Factor Analysis[31]of seven individual objectives of AMT use included in the questionnaire. We have used 'Principal Component Method' which is a common data reduction technique used in factor analysis to extract principal components from a set of variables[32]. The resulting factor loadings of the objectives of adoption (provided in Table A2 in Appendix A) show two factors, which are the combination of some of the objectives of adoption. The first factor is actually a linear combination of expected product improvements, and cost savings resulting from the use of AMT use such as higher flexibility, improved product quality, reduction in production time etc. We term it as the improvement in product technology (PRODTECH). The second factor is denoted as buyer pressure (BUYERPRESUR) which is a combination of meeting the customers' demands for a greater use of AMTs and securing a technological lead in the market. Both of these factors are assumed to have a positive effect on the adoption of AMTs. Given the technological dependence among the automotive firms and their parts suppliers, greater demands for more quality products from the former can act as an augmenter of the adoption of new technologies like AMTs.

It has been argued that both the length and breadth of external linkages matters for the adoption process. While the diverse sources of external connections of a firm exposes it to a variety of information/ knowledge regarding new technology, an intense linkage would

[29] OEM is used to refer to a company that acquires a product or component and reuses or incorporates it into a new product with its own brand name. It is interesting to note that OEM term originated in the automotive industry.

[30] In fact, this is also related closely to the negative impact of overcapacity in innovative behaviour of firms discussed in the empirical literature.

[31] Factor analysis is applied: (1) to reduce the number of variables and (2) to detect structure in the relationships between variables, that is to classify variables. A hands-on how-to approach on factor analysis can be found in Stevens (1986).

[32] Basically, the extraction of principal components amounts to a variance maximizing (varimax) rotation of the original variable space. The computational aspects of principal components analysis can be found in Stevens (1986).

enable the firm to exploit the resource better. The external linkages of the firms can be captured by the cooperation of the firm with other firms and organisations. We include firms' cooperation with others (COOP) in the areas viz., design, production, research & development, marketing/ export promotion, problem solving, human resource development (e.g., joint training etc.). Higher cooperation in any or all of the above areas could signify the ability of the firm to monitor the development of newer process technologies and increase its ability to assimilate the knowledge. This variable is expected to impact positively on the adoption of AMTs.

From our theoretical framework described above we know that various external factors have been hailed to have significant effect on the propensity to adopt new technologies. We term them as the external stimulators of adoption. Three variables are used to capture the effects of external factors on the adoption process. First, as argued in the previous section, machinery suppliers are important motivators for the firms to adopt AMTs. This is represented by STIM_SUPP, which is defined as a dummy variable if the firms report affirmatively the role of machinery suppliers as motivators of adoption. The second variable is also a dummy variable (STIM_PEER) which is measured as the 'firm visits in the locality'. This is assumed to act as a proxy for the 'epidemic effects' of adoption. We hypothesise that the firm visits to local area to positively affect the adoption process. The third variable that is considered here is the information gain from participation in various forums like trade fairs and other such forums, which is a potential source of external learning about the new technologies. This variable (STIM_EXTINFO) is again denoted by a binary variable.

Another factor that we use to capture the intensity of external learning opportunities is the position of the firm among other firms in its social network, also sometimes known as "social power" (Hanneman and Riddle, 2005). (Social) network thinking emphasizes that power is inherently relational i.e., a consequence of patterns of relations. An individual does not have power in the vacuum; rather he can have power when he can dominate others. Network analysts often describe the way that an individual (actor) is embedded in a relational network power offering power to him. Actors who have more ties to other actors may be in a 'favoured position' as they may have access to, and be able to call on more of the resources of the network as a whole. Alternatively, as they have many ties, they are often third-parties and deal makers in exchanges among others, and are able to benefit from this brokerage.[33] A rather simple, but often very effective measure of an actor's centrality and power potential is given by their degree of association in the network. In this vein, it can be argued that firms who have many ties in their network would be in an advantageous position in the process of knowledge/ information gain. We therefore use the (network) centrality of firms (NETCENT) as another explanatory variable to capture the external learning opportunities of the firms. This is defined in our case as the 'out-degrees'[34] of firms, which imply the number of ties from an auto component firm to buyer firms in the

[33] This is linked to the concept "social capital" (see Burt, 2000 and Coleman, 1990) in network theory.
[34] In network terminology, the degree of a vertex or node is the number of edge connecting to it. Analogously, out degree is defined as the number of ties going out of the vertex to others in the network. In our case, out degrees are the number of firms to which a particular auto component firm has a supply relationship. This is calculated using UCINET 6.2 (software for Social Network Analysis (Borgatti et al., 2002))

network.[35] The effect of this variable is again assumed to be positive as being central to the network i.e., having greater out degree values (e.g., the firm can get access to the resources of its partners) can facilitate the adoption propensity.

5. DISCUSSION OF RESULTS

5.1 Overall AMT Use and Intensity of Adoption

This paper uses the data on the adoption of twelve advanced manufacturing technologies employed in a wide range of functional areas of the Indian auto components firms.[36] It is observed (from Table 1) that all the firms in our sample have adopted at least one or more advanced manufacturing techniques. About 68.5 percent of the firms have used at least one AMT component (out of the 12 listed).[37] Figure 3 lists the constituent AMTs and the associated percentages of actual use. For example, CAD/CAE, in our case, has the highest incidence of use (74.2%) whereas Robots are used only by tiny (8.1) percent of the total firms. As evident (Figure 2), four AMTs, viz., Computer Aided Design/ Engineering (CAD/CAE), Programmable Logit Controllers (PLCs), Computer Numerically Controlled Machines (CNC/DNC), and LAN/WAN systems for engineering and/or Production have an applicability among more than 60 percent of firms. On the other hand, AMTs such as Robots and Rapid Prototyping Systems (RPS) are very far from making their presence in the industry widely. Less than one fifth of the firms have reported to possess any such AMT.

The overall pattern of AMT usage shows that about 69 percent of the total firms have adopted AMTs (see Table 3).[38] An important feature concerning the adoption pattern of AMTs can be gained by considering the size-structure of adopting firms. As would be expected, large firms dominate the use of AMTs (Table 4) and the incidence of AMT adoption is the lowest among the small firms. Overall, there is a positive association between adoption rates and the sizes of the firms (Table 4). More insights on the adoption

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[35] This is constructed from the citations of the auto component firms (which we term as suppliers) about the firms they sell their products to. The firms which buy the components are defined as customer firms. The auto component firms generally sell their products to other automotive firms (viz., manufacturers of vehicles like passenger cars, buses, trucks etc as well as farm equipments and agricultural equipments). Moreover some of these firms also sometimes supply to other firms in other industries e.g., machinery manufacturers as some of the components needed for automotive manufacturing are also important parts for machinery and other equipment production (see Parhi, 2005 for details).

[36] For the ease of analysis and also for the purpose of delineating differences in adoption pattern across technology groups, the AMTs have been aggregated into three complementary categories- each category having some characteristics in common. The categories are called as Software, Hardware, and Network Communications technologies (Baldwin and Sabourin 2002).

[37] The 12 AMTs covered in the survey are: Computer Aided Design/ Engineering (CAD/CAE), Computer Aided Manufacturing (CAD/CAM), Modelling or simulation technologies (MST), Manufacturing Resource Planning Enterprise Resource Planning (MRP/ERP), Computerised Production Planning System (CPPS), Computer numerically controlled machines (CNC/DNC), Programmable Logic Controllers (PLCs), Robots, Rapid Prototyping Systems (RPS), Electronic exchange of CAD files (ECAD), Other Network Systems (e.g., LAN, WAN), Inter-company computer networks (ICCN). These were classified into three complementary technology classes viz., software, hardware and network communications.

[38] Given the heterogeneity in the complexity levels of the various AMTs in our list, we use the criterion 'adoption of at least one technology from each of the three technology groups' (Baldwin and Sabourin, 2002).

pattern and their dynamics will be clear from the econometric results explained in the following paragraphs.

The results of logistic regression[39] for AMT adoption are reported in Tables 5 and Table 6.[40] Table 5 presents regression results when the dependent variable is ‘Adoption of at least one AMT element from each of the technology groups’ (AMTTHREE), as described in the preceding section. The ordered logit regression results for intensity of adoption (AMTINT) as dependent variable are reported in Table 6. Three different types of model distinguish our specification and encompassing of variables in order to describe adoption behaviour. Structural model (Model 1a and 1b) comprise of the set of variables, which define the basic structural characteristics of the firms, for instance, firm-size, age of the firm, level of technology in use, R&D, and the stock of human capital. Models 2 and 3 evince broader encompassing as we gradually add market dynamics and interactions in the structural model.

The first model in Tables 5 and 6 is the ‘structural model’, which in fact defines a “closed” adoption model, while the Full model (with interaction and market dynamics in Model 3), describes a ‘socio-economic’ model due to the fact that economic conditions are best reflected with market dynamics and social conditions are represented by interaction with buyers, similar firms, and access to ‘external information channel’, etc. Our idea is thus to study the adoption behaviour of firms step-wise including more dynamics at each step. The formalisation remains the same for regression with adoption intensity so as to make appropriate comparisons to better understand the effects of various factors.

A closer look at the results presented in Tables 5 and 6 show that all classifications of determinants we postulated in section 4.3, despite having magnitudes of varying size and effects on adoption exert significant impact on the adoption process. The significance of the determinants, therefore, needs more elaborate delineation to establish their possible impact on the probability of adoption of new technologies, which is the central objective of this paper.

From the first columns of Tables 5 and 6 it can be observed that as expected, the coefficients of structural variables are positive and statistically significant at $p < .01$ level.[41] Evidently, large and medium sized firms are more likely to adopt AMTs. In accordance with the standard result in the literature, the probability of adoption is much higher for large firms than small firms. Similarly, firms with a greater number of years in operation have greater odds of adopting new technologies. In other words, old firms are more likely to invest in new technologies like AMT. This evinces the conjecture that the age of the firm is positively correlated with the experience in machining technologies that put the firm in a better position to adapt to the newer technologies. Apparently, it strengthens the ‘experience effect’ of older firms over the ‘adjustment cost’ of investing in new technologies. All the variables are also jointly significant in the model which evinces the positive impact of the structural parameters on the adoption process. The basic pattern

[39] All estimations have been performed using STATA 8.2.

[40] The summary statistics for all variables is provided in Table A1 in the appendix.

[41] Surprisingly RND is not found to be significant in the adoption intensity model. We try to give some intuitive reasons later in this section regarding the possible non-significance of this variable in the model.

of the results remains quite the same in both AMT adoption propensity and the intensity of AMT use, thus pointing to the robustness of the rank effects captured in our model.

To lend exact interpretation of the magnitudes of change of explanatory variables on AMT adoption, the estimated odds-ratios (which are nothing but the exponential expression of the coefficients in Table 5 and 6) are presented in Tables 7 and 8 respectively. It may be noted that the odds of increase in adoption due to a unit change in firm size (i.e., moving from a small to medium or large size) are about 23.68 (see Table 7). Firm age matters, however, the odds are more or less evenly distributed. For AMT intensity also we find similar pattern for firm age.

Similarly, QUALEMPL, RND and TECHLEVL are positively related to the probability of adoption (Tables 5 and 6 (except RND here)), which supports our argument that a greater internal capability would enhance the probability of adoption and therefore is a significant determinant of technology adoption. New technologies involve great uncertainties. Eventually firms possessing superior internal capability (or, absorptive capability) in the form of higher current level of technology used, richer stock of human capital (skilled workers) etc. would be in a better position to adopt and implement AMTs. We find that the current level of technology (TECHLEVL), the availability of skilled labour (QUALEMPL) as well as RND are highly statistically significant in explaining AMT adoption propensity (Table 5), thus supporting our argument. Table 7 also complements this conjecture by depicting that, the odds for AMT adoption is about 6.9 unit against a unit change in current level of technology (TECHLEVL). Similarly, an increase in R&D performance is likely to enhance the adoption odds by about 5.3 times (see Table 7). Similar inferences can be drawn for the adoption propensity (See Table 8).

An interesting outcome is observed for RND as this variable is not found to exert statistically significant impact on the intensity of AMT adoption though its influence is positive.[42] The estimated odds-ratio also suggests that a unit change in RND (i.e. moving from no R&D to R&D practices) would bring about more than one point change in AMT adoption. However, the odds ratio for RND is not so high compared to that of other variables. In our view, the statistical non-significance though, does not belittle the importance of R&D for innovation, plainly shows this might not be so crucial in the presence of other related variables like QUALEMPL and TECHLEVL which probably proxy the absorptive capacity in a better way in our model. Moreover, it can also be perceived RND along with other firm-specific variables are jointly significant (in case of AMTINT model) which proves the overall impact of the structural parameters.

The impact of market dynamics is shown to be significant only in terms of the size of the market base (MKTBASE). Broader market base of the firms (catering to the foreign firms in addition to the domestic ones) positively impacts on the propensity to adopt AMTs. Indeed, this base instils an air of competition and high demand for quality product, which ostensibly initiates firms to go for better technologies. The impact of the competition (NCOMP) though not found to be statistically significant, is found to have a positive

[42] It may be pointed out that R&D and size variable seems to be highly correlated as large firms tend to have more regular R&D practice for which the effect of R&D is not coming out to be significant.

impact on both adoption and its intensity. This is in line with the theoretical argument that competition is beneficial for innovation.

The adoption of AMT is found to be positively influenced by the BUYERPRESUR giving an apparent role to the buyers' (automotive firms) on adoption. It is clear from Table 3 and 4 that greater demands by automotive firms for better quality components and pressure from industry motivate the firms to adopt AMTs. From Table 7 it is evident that the odds of AMT adoption due to buyer pressure is 2.25, implying that a unit change in buyers demand would increase AMT adoption by about two and half times. This is also the case in the intensity of adoption where the odds of adopting more AMTs (being in a higher intensity category) are significantly greater than 1. The objectives / motivations for meeting the buyers/ industry demand and improving the product quality are also jointly significant. In fact it sounds plausible too as a stringent quality requirement for auto parts from automotive firms forces a certain degree of pressure on component firms to go for better technology and therefore acquire advanced process technologies. Thus, the demand pressure exerted by buyers not only motivates the firms to invest in advanced technologies but also allows them to go for more intensive use of these. In fact, an indicative and impressive role for the buyers and the need to be closer to them also comes out very distinctly from the micro-level analysis of the survey data. The significance is also ascertained in the estimated equations of AMT adoption and intensity of use. This is a very important finding as it points to a 'demand-led' adoption/ innovation process in the industry.

The diversity and intensity of firms' external resources also influence AMT usage positively as can be seen from model 3 results (last columns of Table 5 and Table 6). Though all of the variables in this category seem to favour adoption propensity (except STIM_PEER in Table 6) positively, the number of active external learning sources such as participation in trade fairs and other such forums proves particularly beneficial for the adoption of these technologies. Participating in trade fairs, and overseas visits make the firms more informative about the available and/or upcoming technologies and give them a more direct way of learning about the usage of AMTs. Therefore, higher is the interaction in forums like trade fairs, higher will be the probability to use AMTs. The other two variables, i.e., COOP and NETCENT though positive are not found to have considerable impact on adoption probability statistically.

The estimated results while dependent variable is the intensity of AMT use (Table 6) are more or less similar to the adoption of AMTs (Table 5). The estimates of adoption intensity (AMTINT) depict that all the structural variables and the ones capturing market dynamics are positive and statistically significant (except NCOMP). However, as can be observed from models 2 and 3 in the table, market dynamics variables are jointly significant verifying the significant impact of the market condition on the intensity of adoption. Additionally, the motives of adoption are also jointly significant in influencing the adoption intensity of AMTs. The significant positive coefficients of the intercept terms in Table 6 can be explained as an increased chance that a firm with a higher score on any explanatory variable (viz., QUALEMPL) will be observed in a higher intensity category.

5.2 Predicted probabilities of adoption

Figure 4 depicts the predicted probabilities of AMT adoption due to the changes in some key determinants of adoption.[43] The probabilities here refer to the predicted values of adoption by a specific explanatory variable, holding all other variables constant at specified values (defaulting to the mean).The figures reflect the effect of change in one of the explanatory variables on the predicted probability of AMT adoption keeping others constant in the process.

Consider first, the effects of changes firm size and in the stock of human capital on the predicted probability of adoption. From Figure 4 it is evident that the predicted probability of adoption increases linearly with firm size indicating larger firms will tend to adopt more than smaller firms. This might be due to the scale of operation and specialisation of product in the large and small firms. The stock of human capital has been proxied by the percentage of skilled or qualified labourers in the firm. As new technologies involve a complex technological knowledge base in its operation and use, a skilled employee base provides conducive platform for adoption. The third chart in top panel of Figure 4 precisely describes this feature. The model predicts that an increase in the skill level of the auto component firms will increase the probability of adoption. Probability of adoption increases at a decreasing rate.

The technological level of the firm also initiates adoption probabilities. Higher is the technological sophistication in the firm, the higher will be the probability of adoption. In fact the current technological level of the firm (named as ‘Absorptive Capacity’ in the Figure 4) indicates the stock of technological capability (which could be from the past experience of the firm) and therefore significantly affects the technological activities (such as using or developing new technologies). From the graph it can be marked that the predicted probabilities increase linearly with the amount of technological level.

Interesting cases emerge for adoption probability due to the age of the firms. Conforming to the theoretical convention, the prediction indicates that as the age of a firm will increase, the probability of adoption will also increase, though at a decreasing rate. An older firm is a storehouse of experience; since the firm has gathered experience due to long operation in the market over the years, it gives the firm an edge to rule in the uncertain market conditions. Higher age of the firm indicates greater length of sustainability in the market and therefore a continuous pressure on renovating product and process compelling/ motivating the firm to adopt new technology. Older firms have therefore greater probabilities of adoption.

Buyer’s demand and external information sources like participating in trade fairs, keeping up with new information through publications, etc., have significant positive effect on the probability of adoption as depicted by Figure 4. Here also, the probability of adoption increases at a decreasing rate. External information sources (‘External Learning’ in Figure 4) also have pervasive effect on the predicted probability of adoption, which increases linearly with changing mean level of source of external information. This is because

[43] We have used STATA 8.2 package to estimate the predicted probabilities. It may be noted that the predicted values are generated for the most general model (conforming to model 3 in our analysis)

external learning and interaction opportunities, say participation in trade fairs, etc., also make the firms more informative about the available and/or forthcoming new technologies in the market. Therefore, higher is the interaction and greater is the strength of external linkages, higher will be the motivation to adopt AMTs. In fact, external learning and interaction monitor the 'information channel'. Quality and prospective information is a great motivator of adoption. However, if the firm has poor stock of human capital and low technological level, then synergies of external learning can not be effectively internalised to give the firm the *big push* for adopting AMTs. From our survey it is evident that the firms who have significantly higher technological capability and a greater percentage of skilled labour have a greater possibility of using the 'information resources', thus leading to higher adoption.

Another interesting feature stems from the effect of cooperation on the probability of adoption. It is apparent from Figure 4 that higher cooperation in fact yields greater probability of adoption when other variables are held constant. The underlying idea is that by cooperation firms might be able to sort out complexities involved with new technologies and therefore could jointly minimise a large part of the expected risks endowed with new technology adoption.

6. SUMMARY AND CONCLUSIONS

The central idea in this paper was to investigate the effect of main determinants of the AMT adoption in Indian Auto component industry. Traditional studies on the adoption of new technologies focussed to a great extent on the micro-economic determinants, viz., firm-specific characteristics, in part because they have proved to be crucial in explaining the broad patterns of technology diffusion. Recent efforts in this regard have tried to look beyond the structural characteristics and have encompassed the socio-economic features to map out a better understanding of the diffusion dynamics. Drawing on the recent developments, the objective in this exercise has been to identify and evaluate the relevant factors determining the pattern of AMT adoption in Indian automotive industry. Our empirical foundation therefore, has been built around the traditional firm characteristics as well as the recent convention of socio-economic environment consideration. The exhaustive framework has equipped us with interesting findings about the adoption behaviour of AMTs in the Indian context, which would enable us to have a thematic outlook of the actualities in the Indian automotive industry.

Our analyses confirm most of the theoretical and empirical predictions about the adoption of technology advanced in the literature. It emerges from the analyses that structural characteristics of the organisation remain as crucial variables for the use of new technologies due to their sheer impact on the economic viability of the large investment in them. Larger firm size coupled with a richer stock of its human capital base is found to give a potential edge to firms to become more innovative. Moreover, a greater investment in R&D is also seen to greatly enhance the adoption of new technology diffusion. The results strongly supports that greater internal resources enable the firms to better innovate in the economy. The results, thus generally confirm the conventional wisdom about the determinants of adoption.

Given the recent dynamical changes occurring in the market, it is imperative to consider that broader market base influence the adoption patterns of new technologies. Our results with market base confirm this premise and opens up direction for more explicit consideration and study of market dynamics in the adoption model. An important facilitator of adoption found in the exercise is buyers' pressure. This conjecture has recently found prominence in the diffusion literature as it is held that demand side uncertainties are as crucial as technological uncertainties as determinants of adoption. A peculiar feature of developing countries market structure is that it is characteristically weak as imperfections of many kinds, beginning from the nature of buyers demand and structural bottlenecks imposed by the economy etc., stifle the innovative behaviour. The demand side uncertainty is mostly reflected in buyers' demands; hence a better management of buyers' pressure would greatly improve the innovative ability of the firms.

Moreover, the adoption behaviour of the firms is closely linked to its socio-economic environment. It is evident from our results that cooperation variables as well as external motivators have significant effect on AMT adoption. These socio-economic variables such as cooperation with other firms and the exposure effective external learning forums greatly contributes the firm's ability to evaluate and better implement the newer process technologies. The diversity and quality of external sources of learning therefore needs to be further scrutinised so that appropriate policies can be drawn to further their impact on adoption/ innovation.

To summarise, we found the pivotal role of the conventional firm-specific factors conforming largely to the established empirical literature in the developed country settings. The similarity of the results for Indian case reflects that irrespective of the 'degree of development', the likelihood of a firm's decision to adopt a new technology will be conventionally dependent on its own characteristics (which are described as 'supply side or productivity-related' side of determinants). More interesting results emerge as we enlarge our model by inducting market dynamics and socio-economic variables. Indeed, greater breadth of market was found to be stimulant for adoption and when other socio-economic indicators are used we also found the consistent effect of buyers demand on adoption decision. This finding, as a result of extension of traditional model of diffusion and determinants of adoption has significance for developing countries like India as growing market as well as buyers demand is natural consequences of an emerging economy.

A deep insight into the results point to the fact that decision to adopt a new technology is indeed multi-dimensional in nature, affected to a great extent by firms' own ability to stand up to market demand, their absorptive capability, and also factors in the broad environment such as quality of infrastructure, market base etc. This reiterates the systemic features of the diffusion process and the need for targeted policy efforts in tackling the deficiencies in the system in order to encourage faster diffusion.

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List of Tables and Figures

Table 1a: Description of Dependent variables (Adoption and Intensity of Adoption)

Dependent Variable	Variable Definition	Nature of Variable
Propensity of Adoption		
AMTTHREE	Adoption of AMTs: Adoption of at least one from each of the three groups of AMTs (software, hardware and network communications). AMTTHREE = 1, if adopted =0, if not adopted	Dichotomous
	Intensity of Adoption	
AMTINT	Intensity of adoption of AMTs : Total number of AMTs adopted (grouped into four intensity categories), viz., AMTINT: 0-3, 4-6, 7-9 and >9 with values 1 to 4 for the lowest and highest intensity respectively). AMTINT = 1, if the firm adopted between 0-3 AMTs = 2, if the firm adopted between 4-6 AMTs = 3, if the firm adopted between 7-9 AMTs = 4 if the firm adopted between >9 AMTs	Polychotomous

Table 1b: Definition of independent variables

Explanatory Variables	Definition	Nature of Variable
FIRMSIZE	Size of the Firms: Defined on the basis of number of employees; < 100 employees is considered as small and >100 is considered as large firm. FIRMSIZE = 1, if large = 0, Small	Dichotomous
FIRMAGE	No of years the firm has been in operation till survey date (2003). Note: Calculated as 2003 minus the starting year of firm's production.	Continuous
QUALEMPL	Percentage of Employees with technical /managerial experience.	Continuous
TECHLEVL	Level of Technology. It is defined as firm's own assessment of its current product and process technology level. Originally a scale variable (1-5), this variable has been converted to a binary variable defined as: TECHLEVL = 1, if firms' assessment in both process and product technology is >3 = 0, Otherwise	Dichotomous
RND	R&D performance by the firms. RND = 1, if the firm conducts R&D = 0, otherwise Note: No R&D = 0, Occasional and Regular R&D = 1	Dichotomous
MKTBASE	Broadness of the market served by the firm (Based on the domestic versus foreign OEM status of the firm) MKTBASE = 1, if the firm is an OEM supplier to	

	both domestic and foreign (within and outside India) automotive firms. = 0, if the firm is an OEM supplier to only domestic automotive firms.	Dichotomous
NCOMP	Competition in the firms' product market (in the main product class). Scale variable in the original data transformed here as per the following rule: NCOMP = 1, if firm has competitors in the industry = 0, otherwise	Dichotomous
PRODTECH	Objectives/motives for the adoption of AMTs: Product technology improvement Combined factor score of: Process time reduction, product quality improvement, and flexibility enhancement. Note: See factor analysis table for the details.	Continuous
BUYERPRESUR	Objectives/motives for the adoption of AMTs: To respond to customers/ industry pressure. Combined factor score of: As response to demands by customers to use AMTs, and peer pressure (e.g., competitors introduce AMTs) Note: See factor analysis table for the details.	Continuous
COOP	Co-operation (Low Vs High cooperation with other firms). COOP =1, if the firm cooperates highly = 0, Otherwise Note: A scale variable, made binary using the criterion of high and low cooperation (based on total score on all areas of cooperation).	Dichotomous
STIM_SUPP	External Stimulators of adoption: Machinery Suppliers STIM_SUPP = 1, if Machinery suppliers have stimulated adoption = 0, Otherwise	Dichotomous
STIM_PEER	External Stimulators of adoption: Local Firm Visits STIM_PEER = 1, if local firm visits have stimulated adoption = 0, Otherwise	Dichotomous
STIM_EXTINFO	External Stimulators of adoption: External Information sources (Trade fairs etc.) STIM_SUPP = 1, if Trade fairs and other external information have stimulated adoption = 0, Otherwise	Dichotomous
NETCENT	Network centrality of the firm: Degree centrality (Outdegree) values for each firm. NETCENT= 1, if the firm is considered to be prominent in the network i.e., has higher outdegrees than average (>10) = 0, otherwise	Dichotomous

Table 2: Determinants of Adoption: Expected Impact in the analysis

Factors determining diffusion of AMTs (Indicators or Proxies to Measure)	Variables Name	Expected signs
Firm-specific variables		
1. Firm-size	FIRMSIZE	+
2. Age of the firm (The number of years the firm has been in operation till the year of the survey)	FIRMAGE	?
Absorptive capability (or internal capability of firms)		
1. Percentage of Employees with technical/ managerial experience	QUALEMPL	+
2. R&D performance	RND	+
3. Accumulated technological base (Current level of technology)	TECHLEVL	+
Market Dynamics		
1. Presence of competition in the market	NCOMP	?
2. Broadness of the market served by the firm	MKTBASE	+
Demand/ Technology Factors		
1. Product technology improvement	PRODTECH	+
2. To respond to customers/ industry pressure	INDPRESUR	+
Diversity and Intensity of External Resources		
1. External Stimulators		
- Industry Association, Consultants etc.	STIM_SUPP	+
- Peer group (epidemic effect)	STIM_PEER	+
- Knowledge exchange through trade fairs, publications, overseas firm visits, etc.	STIM_EXTINFO	+
2. Co-operation with other firms (in design, joint production, R&D, joint problem solving, joint training etc.)	COOP	+
3. Network centrality of the firm	NETCENT	+

Table 3: Incidence of AMT Usage

AMT Usage	At least one AMT from each technology group	
	N	%
Adopted	85	68.5
Not Adopted	39	31.5
Total	124	100

Source: Own calculation from survey data

Table 4: AMT Use Across Firm Sizes

Firm-Sizes (No. of Employees)	Adopted		Not-adopted	
	N	%	N	%
Small (<100)	6	7.06	25	64.10
Medium (100-250)	22	25.88	11	28.20
Large (>250)	57	67.06	3	7.69
Total	85	100	39	100
Chi-square (with 2 d.f) = 54.32				

Source: Own calculation from survey data

Table 5: Logistic Regression Results for AMT adoption:

(Dependent Variable: AMTTHREE)

Explanatory Variables	Model 1 Structural Model	Model 2 Market Dynamics	Model 3 Interactions Model
1. Internal Factors and Absorptive Capability			
FIRMSIZE	3.164*** (0.664)	2.787*** (0.748)	2.501*** (0.961)
FIRMAGE	0.067*** (0.025)	0.053** (0.025)	0.035 (0.024)
TECHLEVL	1.876*** (0.719)	2.283*** (0.868)	2.489*** (2.52)
RND	1.674** (0.846)	2.065*** (0.788)	2.308*** (0.945)
QUALEMPL	0.052*** (0.016)	0.043*** (0.016)	0.036** (0.018)
2. Market dynamics			
MKTBASE	--	1.929*** (0.805)	1.974** (1.017)
NCOMP	--	1.046 (0.973)	0.655 (1.293)
3. Demand/Technology Factors			
PRODTECH	--	--	0.016 (0.362)
BUYERPRESUR	--	--	0.811* (0.432)
4. Social and External Resources			
COOP			0.806 (1.031)
STIM_SUPP	--	--	0.291 (0.965)
STIM_PEER	--	--	1.096 (0.792)
STIM_EXTINFO	--	--	1.529** (0.760)
NETCENT	--	--	0.241 (0.829)
Intercept	-7.633*** (1.540)	-9.431*** (1.913)	- 10.532*** (2.192)
N	122	122	111
Mc Fadden R^2	0.505	0.572	0.615
Wald Chi-Square	41.05***	39.16***	39.35***

Note: (1) {} implies joint significance (by Wald Test). (2). ***, **, and * represent significance at $p \leq 0.01$, $p \leq 0.05$ and $p \leq 0.10$ respectively. (3) Bracketed values are robust standard errors.

Table 6: Ordered Logistic Regression Results for AMT Adoption

Dependent Variable: AMTINT

Explanatory Variables	Model 1 Structural Model	Model 2 Market Dynamics	Model 3 Interactions Model
1. Internal Factors and Absorptive Capability			
FIRMSIZE	2.782*** (0.648)	2.306*** (0.724)	2.190*** (0.720)
FIRMAGE	0.019* (0.011)	0.011 (0.011)	0.010 (0.015)
TECHLEVL	1.303*** (0.444)	1.670*** (0.484)	1.835*** (0.530)
RND	0.527 (1.153)	0.658 (0.932)	0.665 (1.127)
QUALEMPL	0.020*** (0.007)	0.0161** (0.007)	0.013 (0.008)
2. Market dynamics			
MKTBASE	--	1.850*** (0.470)	1.940*** (0.483)
NCOMP	--	0.294 (0.440)	0.430 (0.766)
3. Demand/Technology Motivators			
PRODTECH	--	--	0.369 (0.291)
BUYERPRESUR	--	--	0.372* (0.215)
4. Social and External Resources			
COOP	--	--	0.606 (0.495)
STIM_SUPP	--	--	0.343 (0.593)
STIM_PEER	--	--	- 0.460 (0.422)
STIM_EXTINFO	--	--	0.832* (0.516)
NETCENT	--	--	0.172 (0.500)
Intercept 1	3.627*** (1.198)	4.625*** (1.087)	5.445*** (1.538)
Intercept 2	5.380*** (1.266)	6.626*** (1.179)	7.652*** (1.642)
Intercept 3	7.501*** (1.365)	8.925*** (1.307)	10.057*** (1.786)
N	122	122	111
Mc Fadden R^2	0.211	0.266	0.281
Wald Chi-square	47.53***	68.36***	69.62***
LR test of proportionality of odds: Chi-square	11.06*** (df = 10)	13.21*** (df = 14)	32.24*** (df = 28)

Note: (1) {} implies joint significance (by Wald Test). (2) ***, **, and * represent significance at p ≤ 0.01, p ≤ 0.05 and p ≤ 0.10 respectively. (3) Bracketed values are robust standard errors.

Table 7: Odds-Ratio for the Logistic Regression for Adoption Propensity

(Dependent Variable: AMTTHREE)

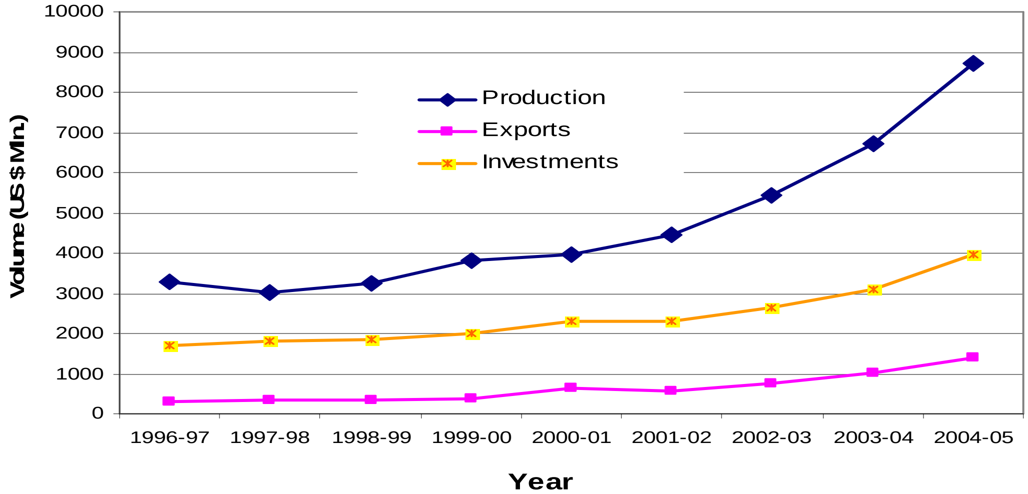
Explanatory Variables	Model 1 Structural Model	Model 2 Market Dynamics	Model 3 Interactions Model
FIRMSIZE	23.684	16.234	12.199
FIRMAGE	1.069	1.054	1.036
TECHLEVL	6.532	9.810	12.051
RND	5.335	7.890	10.061
QUALEMPL	1.054	1.044	1.037
MKTBASE	--	6.887	7.206
NCOMP	--	2.846	1.925
PRODTECH	--	--	1.016
BUYERPRESUR	--	--	2.250
COOP	--	--	2.239
STIM_SUPP	--	--	1.338
STIM_PEER	--	--	2.992
STIM_EXTINFO	--	--	4.616
NETCENT	--	--	1.273

Table 8: Odds-Ratio for the Logistic Regression for Adoption Intensity

(Dependent Variable: AMTINT)

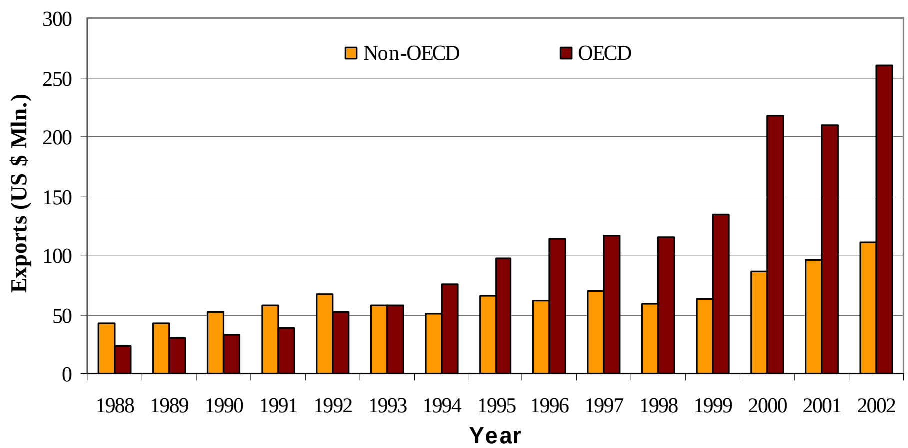
Explanatory Variables	Model 1 Structural Model	Model 2 Market Dynamics	Model 3 Interactions Model
FIRMSIZE	16.165	10.036	8.939
FIRMAGE	1.019	1.011	1.010
TECHLEVL	3.682	5.314	6.269
RND	1.695	1.931	1.945
QUALEMPL	1.020	1.016	1.013
MKTBASE	--	6.360	6.962
NCOMP	--	1.341	1.537
PRODTECH	--	--	1.446
BUYERPRESUR	--	--	1.450
COOP	--	--	1.834
STIM_SUPP	--	--	1.409
STIM_PEER	--	--	0.630
STIM_EXTINFO	--	--	2.299
NETCENT	--	--	1.188

Figure 1: Trends in Production, Investment and Exports



Source: Own construction from ACMA data.

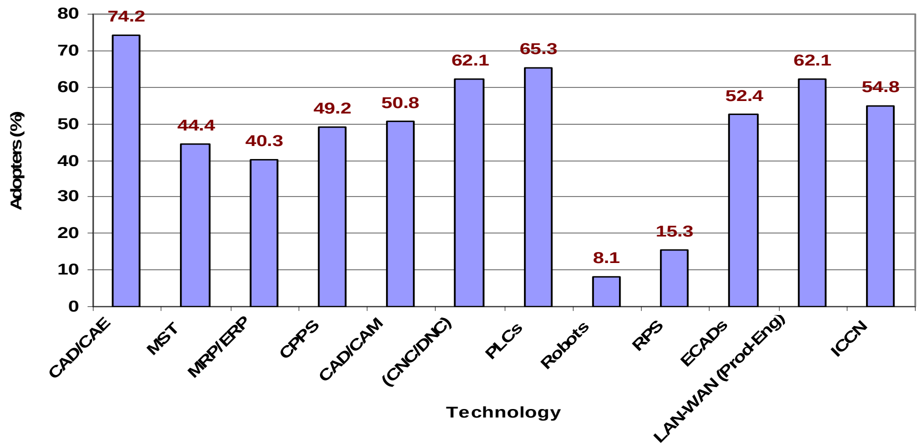
Figure 2: Direction of Exports of Auto Components Industry



Source: Own calculation from UN COMTRADE[44] data

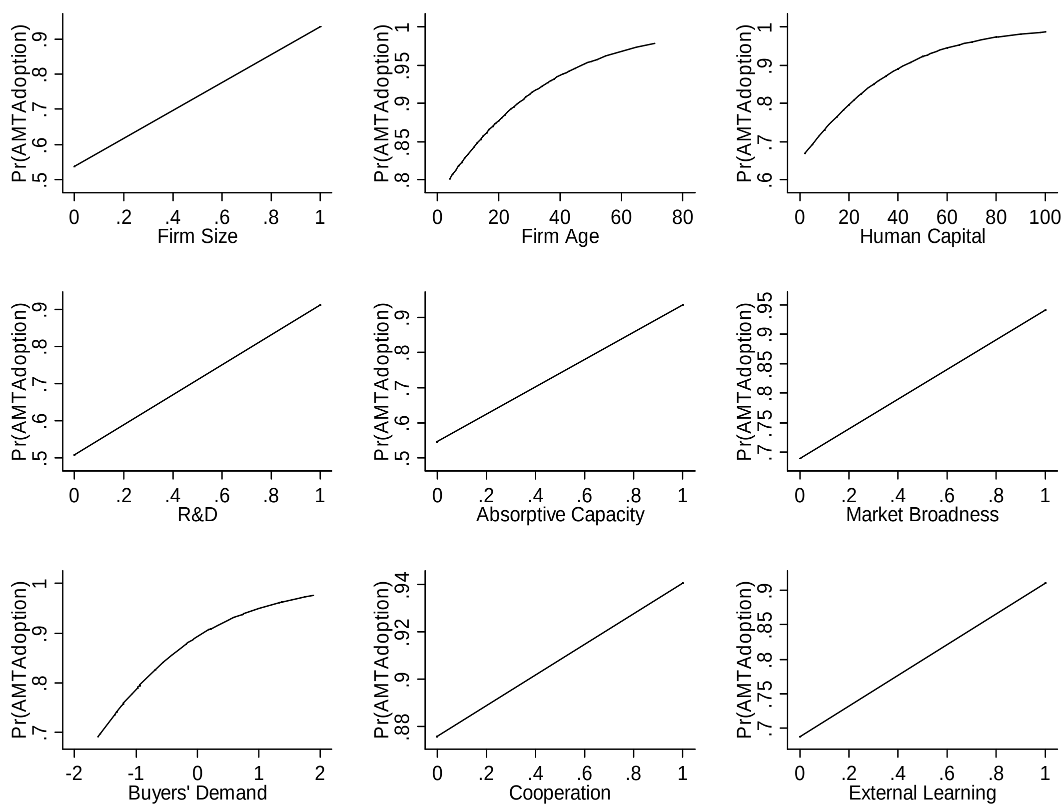
[44] UN COMTRADE (United Nations Commodity Trade Statistics Database) contains trade data (imports, exports and re-exports) from countries world-wide. For each country annual data can be retrieved by commodity and trading partner. Commodity is defined by either standard international product (SITC) codes. The data used in our analysis refers to the SITC Revision 3 data for category 7843 (Other parts, motor vehicles). For more details see http://unstats.un.org/unsd/comtrade/.

Figure 3: Proportion of AMT Adopters (By Technologies)



Source: Own construction from survey data. N=124

Figure 4: Prediction of Adoption Propensity



Note: All other variables set to sample means for constructing the predicted probabilities for each of the variables.

Appendix A

Table A1. Summary statistics of variables

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Dependent Variables					
AMTTHREE	124	0.685	0.466	0.00	1.00
AMTINT	124	2.315	1.039	1.000	4
Explanatory Variables					
FIRMSIZE	124	0.75	0.43	0.00	1.00
FIRMAGE	122	24.56	14.25	4.00	71.00
QUALEMPL	124	0.40	0.24	0.02	1.00
RND	124	0.90	0.30	0.00	1.00
TECHLEVL	124	0.75	0.43	0.00	1.00
MKTBASE	124	0.64	0.48	0.00	1.00
NCOMP	124	0.96	0.20	0.00	1.00
PRODTECH	124	0.00	1.00	-2.95	0.98
BUYERPRESUR	124	0.00	1.00	-1.61	1.89
COOP	124	0.20	0.40	0.00	1.00
STIM_SUPP	124	0.69	0.46	0.00	1.00
STIM_PEER	124	0.52	0.50	0.00	1.00
STIM_EXTINFO	124	0.88	0.33	0.00	1.00
NETCENT	111	0.44	0.50	0.00	1.00

Table A2: Factor Analysis of the Objectives of Adoption

Objectives	Rotated factor loadings 1	Rotated factor loadings 2	Uniqueness
To reduce costs in general (labour, capital, and material costs)	**0.740**	0.066	0.449
To reduce process time	**0.775**	0.266	0.329
To improve product quality (conformance, precision etc.)	**0.826**	0.110	0.305
To improve flexibility (of work organization, process control)	**0.568**	0.355	0.552
To respond to demands made by customers to use AMTs	0.219	**0.848**	0.234
To respond to peer pressure (e.g., competitors introduce AMTs)	0.068	**0.864**	0.248
To secure technological lead in the market	**0.566**	0.247	0.618

Note: Only factors loadings of 0.4 and more are considered in the analysis.